From wall measurements to three-dimensional turbulent-flow fields

A. Cuéllar Martín [1], A. Güemes [1], A. Ianiro [1], R. Vinuesa [2], O. Flores [1] and S. Discetti [1]

[1] Aerospace Engineering Research Group, Universidad Carlos III de Madrid, Leganés, Spain
[2] FLOW, Engineering Mechanics, KTH Royal Institute of Technology, Stockholm, Sweden

key-words: Turbulence, Simulation

Linear methods have successfully reconstructed turbulent flow fields in channel flows using wall measurements up to the logarithmic region [1]. However, deep neural networks have been developed more recently to incorporate non-linear effects, leading to improved accuracy. In particular, generative adversarial neural networks (GANs) have recently outperformed standard convolutional neural networks in this task [2, 3, 4]. Accurately estimating turbulent flow fields from wall-embedded sensors is crucial for implementing boundary-layer flow control, and deep neural networks improve modeling of the non-linear relationship between wall and flow data.

The aim of this research is to use (GANs) to directly estimate 3D turbulent channel flows from wall-shear stress and pressure measurements. This work builds on previous research on the estimation of wall-parallel planes (which requires separate training for each plane) and extends it to full one-shot 3D estimation. Despite being computationally more demanding, we show that a similar network with a moderate increase in training parameters can provide accurate 3D predictions at a comparable cost to previous 2D implementations. The goal of this research is to pave the way for a more efficient flow estimation from wall sensors.

GANs consist of two networks that compete against each other during the training process. With an analogous implementation to that found in [4], the generator network takes wall measurements of pressure and wall-shear stress as input to generate the 3D velocity field, while the discriminator network is trained to determine if a given flow field is original or if it was created by the generator. In this study, the GANs used 3D convolutional layers to address this specific setup, and the main components of the generator network were the residual blocks which included these convolutional layers.

The dataset used was generated by a direct numerical simulation (DNS) of a turbulent open-channel flow at friction-based Reynolds number of 200 with dimensions of πh in the streamwise direction, $\pi/2h$ in the spanwise direction and $2h$ in the wall-normal direction, with 64, 64 and 128 grid points respectively.

The network can predict the flow field with a slightly higher error level if compared to the 2D single-plane estimation, but with the added advantage of being able to predict many wall-parallel layers at once, which makes the process more efficient. As expected, the velocity fluctuations are estimated with a high accuracy in the viscous layer, then the estimation worsens progressively through the buffer and logarithmic layers. This limitation is also observed in 2D GANs and linear methods, and is attributed to the physical limitation of small-scale structures having a limited impact on the wall measurements.

For one of the test cases used in this work, the volume of the DNS domain up to $y^+ = 40$ was predicted using the first 32 wall-normal layers of the DNS simulation, starting from the wall. Although the mean squared error (MSE) of the prediction 1 is slightly higher than the results in reference [4], the 3D GANs architecture used in this study has a relatively smaller number of parameters (9 million) when compared to the increase in output size, as it predicts 32 layers at once instead of one (1 million).

The figures 2 and 3 present the prediction of the flow field at two different distances from the wall. The network can predict the patterns and structures in the flow field, and its capability to make predictions is better close to the wall than in the center of the channel. This is due to the reduction in the intensity of the structures and the filtering of smaller scales as the distance from the wall increases. The smaller scales cannot be reconstructed beyond a certain point, which depends on the distance from the wall and the patterns present in the wall measurements.

ACKNOWLEDGEMENTS

This contribution has received funding from the Spanish Ministry of Universities under the *Formación de Profesorado Universitario (FPU) 2020* programme, and from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No 949085, NEXTFLOW).

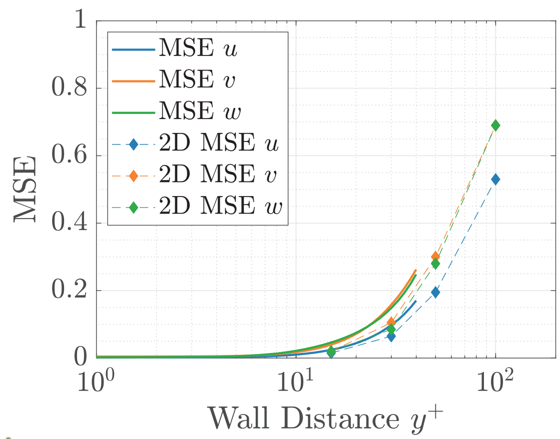

Figure 1: MSE of the prediction of the three components of the velocity fluctuations as a function of the inner-scaled wall-normal coordinate y^+. The 3D prediction (solid lines), and the 2D prediction from the Ref. [4] (dotted lines) at $y^+ = [15, 30, 60, 100]$.

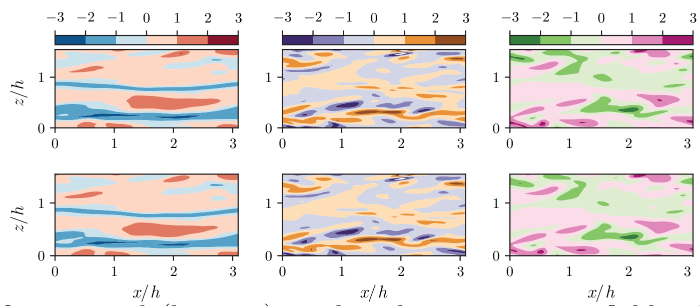

Figure 2: (Top) Reference and (bottom) predicted instantaneous fields of (left) u, (middle) v and (right) w, for $y^+ = 10$.

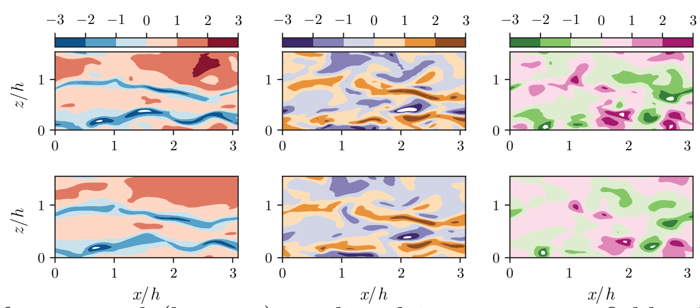

Figure 3: (Top) Reference and (bottom) predicted instantaneous fields of (left) u, (middle) v and (right) w, for $y^+ = 40$.

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